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ARTIFICIAL INTELLIGENCE IN PHOTOGRAMMETRIC MEASURING AND MODELLING OF LANDSLIDE EVENTS

Abstract: Landslides are among the most devastating natural hazards worldwide, causing significant loss of life, infrastructure damage, and economic disruption. Accurate detection, mapping, and modeling of landslides are essential components of disaster risk reduction and sustainable land management. In the past, finding and studying landslides depended on field mapping and subjective visual interpretation of aerial photography. While these methods established a theoretical foundation for understanding slope dynamics, they were often constrained by limited spatial resolution, high labor costs, and an inability to provide timely insights in rapidly changing landscapes. The contemporary transition toward automated, data-driven methods is characterized by the connecting of high-resolution remote sensing platforms – such as Unmanned Aerial Vehicles (UAVs) and sophisticated satellite constellations – with advanced machine learning (ML) and deep learning (DL) algorithms. This change has made it possible to measure movements of the ground and identify areas at risk for landslides more accurately than ever before. Recent advancements in artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL) techniques, have revolutionized the processing and interpretation of photogrammetric data. This synergy facilitates improved landslide monitoring, early warning, and risk assessment, contributing to more effective emergency reaction. This paper aims to emphasize both the advantages and limitations of these technologies in advancing landslide science and disaster management.

Keywords: photogrammetry, remote sensing, artificial intelligence (AI), unmanned aerial vehicles (UAV), landslide monitoring

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Introduction

Landslides represent one of the most destructive geomorphic hazards globally, causing thousands of fatalities annually and inflicting billions of dollars in infrastructure damage and economic losses (Ghorbanzadeh et al., 2019; Kariminejad et al., 2024). These mass-wasting events occur across diverse geomorphological settings – from steep mountainous terrain to coastal slopes and loess plateaus – and are triggered by factors including intense rainfall, seismic activity, anthropogenic disturbance, and progressive slope weakening (Sevgen et al., 2019; Cheng et al., 2021). Accurate and timely detection, mapping, and monitoring of landslides are fundamental to disaster risk reduction, land-use planning, emergency response, and long-term hazard mitigation strategies (He et al., 2022; Zhu et al., 2025). Historically, landslide inventories relied on work-intensive field surveys and manual interpretation of aerial photographs – approaches that provided a foundational understanding of slope dynamics but were constrained by limited spatial coverage, subjective delineation, high costs, and an inability to deliver rapid assessments in dynamic post-disaster environments (Karantanellis et al., 2021; Cardenal et al., 2019). The advent of digital photogrammetry and Geographic Information Systems (GIS) in the late twentieth century introduced semi-automated workflows, yet expert interpretation remained central to feature extraction and classification (Sevgen et al., 2019).

The contemporary era is marked by a paradigm shift toward fully automated, data-driven landslide detection and modeling, enabled by the convergence of three technological advances: (1) high-resolution remote sensing platforms, particularly UAVs capable of acquiring centimetric-resolution imagery and generating dense 3D point clouds via Structure-from-Motion (SfM) photogrammetry (Ghorbanzadeh et al., 2019; Cheng et al., 2021); (2) sophisticated deep learning architectures that perform end-to-end feature learning from raw imagery (Su et al., 2021; Shi et al., 2021); and (3) the availability of large-scale, multisource datasets combining optical, topographic, and radar observations (He et al., 2022; Zhang et al., 2023). Together, these developments have dramatically expanded the spatial scale, temporal frequency, and analytical depth of landslide science.

This paper reviews the state of the art at the intersection of AI and photogrammetric landslide science. It examines the evolution of methodological approaches, the dominant deep learning architectures and training strategies in current use, reported performance benchmarks, and the principal limitations and future directions of this rapidly advancing field.

Material and methods

From Manual Mapping to Object-Based Image Analysis. The earliest systematic landslide inventories were constructed through field reconnaissance and manual interpretation of aerial photographs – methods that established the conceptual framework for understanding slope failure mechanisms but were inherently time-consuming and spatially incomplete (Karantanellis et al., 2021). The introduction of digital remote sensing and GIS in the 1990s enabled the overlay of multi-source spatial data and the application of rule-based classification, yet delineation accuracy remained dependent on operator expertise and local knowledge (Sevgen et al., 2019). Object-Based Image Analysis (OBIA) represented the first major step toward automated landslide mapping. By segmenting imagery into spectrally and spatially homogeneous objects and classifying them using shape, texture, and contextual attributes, OBIA workflows substantially reduced manual intervention (Karantanellis et al., 2021). Studies applying OBIA to UAV-derived orthomosaics and Digital Surface Models (DSMs) demonstrated that automated delineation could closely replicate manual perimeters across diverse terrain settings in Greece, Romania, and Turkey (Yavuz et al., 2023). However, OBIA remained sensitive to segmentation parameters and required site-specific tuning, limiting its transferability across landscapes. This transferability constraint represents a fundamental challenge that persists even in contemporary deep learning approaches, underscoring the importance of geographically diverse training datasets.

Classical Machine Learning in Landslide Mapping. The integration of classical machine learning algorithms – including Random Forest (RF), Artificial Neural Networks (ANN), Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and logistic regression – into landslide susceptibility mapping and inventory workflows marked a significant methodological advance. These approaches enabled the statistical modeling of complex, non-linear relationships between terrain attributes and landslide occurrence without explicit physical formulation (Sevgen et al., 2019). According to Sevgen et al. (2019), a systematic performance assessment of logistic regression, ANN, and RF for landslide susceptibility mapping, using pre- and post-event photogrammetric DEMs as validation surfaces, showed that Random Forest consistently outperformed the other classifiers, particularly when topographic derivatives (slope, curvature, and aspect) and hydrological indices were included as predictor variables. Similarly, Karantanellis et al. (2021) evaluated KNN, decision trees, and RF in an object-based framework applied to UAV-derived data, finding that the integration of DSM-derived features into the RF classifier yielded the highest F1 scores among all tested configurations. Despite these advances, classical ML methods require extensive feature engineering, are sensitive to class imbalance, and may not generalize well across geomorphologically distinct study areas without retraining. These limitations motivated the transition to deep learning, which offers automatic hierarchical feature extraction and greater representational capacity (Su et al., 2021).

The Deep Learning Revolution. The application of deep learning to landslide mapping began in earnest around 2019, driven by the maturation of convolutional neural network (CNN) architectures and the growing availability of high-resolution UAV datasets. Ghorbanzadeh et al. (2019) provided an early and highly influential demonstration, applying multiple CNN designs to UAV imagery along a road section in the northern Himalayas, India. Their results showed that CNNs could achieve precision values approaching 90% and mean Intersection-over-Union (mIoU) scores of approximately 74%, substantially outperforming OBIA and classical ML baselines on the same data. Critically, performance was strongly dependent on design choices: window size, input band configuration, and training strategy, a finding that highlights the need for systematic hyperparameter evaluation rather than ad hoc model selection. Subsequent years saw rapid architectural diversification. According to Su et al. (2021), a pixel-wise landslide inventory mapping system (LanDCNN) based on deep CNNs demonstrated that a 25 km^2 area at 0.5 m resolution could be processed in approximately three minutes – a throughput unachievable with manual methods. Shi et al. (2021) combined deep CNNs with change detection modules, exploiting bitemporal image stacks to improve the discrimination of newly formed landslide bodies from stable terrain on Lantau Island and Sharp Peak, Hong Kong. By the early 2020s, encoder–decoder architectures – particularly the U-Net family and DeepLabv3+ – had become the dominant paradigm for semantic segmentation of landslide features. He et al. (2022) proposed a semi-supervised adversarial network that fused spectral and topographic features derived from UAV photogrammetry, improving precision, recall, F1, and mIoU by approximately 13–18 percentage points over a standalone DeepLabv3+ baseline on a dataset from the Meilong gully, China. Șandric et al. (2024) applied U-Net and DeepLab models to high-resolution UAV imagery for automated crack mapping, finding that tile size and masking strategy strongly influenced performance, with F1 scores ranging from approximately 0.79 (64-pixel tiles, no masking) to over 0.93 (512-pixel tiles, masked samples). This sensitivity to preprocessing parameters illustrates that reported performance metrics cannot be interpreted in isolation from methodological context.

More recent work has explored transformer-based architectures, lightweight multi-scale networks, and instance segmentation frameworks. Kariminejad et al. (2024) benchmarked multiple DL segmenters—including ResU-Net, MA-Net, and attention U-Net variants—for landslide and sinkhole detection from UAV imagery in a semi-arid environment in Golestan Province, Iran, reporting best-case landslide F1 scores of up to 0.95 and ResU-Net precision of 0.97. Lu et al. (2024) proposed MS2LandsNet, a lightweight multi-scale CNN with channel attention, achieving F1 of 85.90% and IoU of 75.28% with minimal computational overhead—an important step toward operational deployment on resource-constrained platforms.

Literature selection and review methodology. This review was conducted as a structured, non-systematic literature survey covering the period from January 2019 to May 2025. The lower temporal bound was selected because 2019 marks the emergence of the first high-impact studies applying deep learning to UAV-photogrammetry-based landslide mapping (Ghorbanzadeh et al., 2019; Sevgen et al., 2019; Cardenal et al., 2019), representing a clear methodological inflection point in the field.

Search strategy and inclusion criteria. A comprehensive search was conducted across Web of Science, Scopus, and IEEE Xplore databases using the following keyword combinations: ("landslide" OR "slope failure" OR "mass movement") AND ("photogrammetry" OR "UAV" OR "Structure-from-Motion" OR "SfM") AND ("deep learning" OR "convolutional neural network" OR "CNN" OR "machine learning" OR "artificial intelligence"). The search was restricted to peer-reviewed journal articles published in English. An initial pool of approximately 187 candidate papers was identified; after screening titles and abstracts for relevance to AI-driven photogrammetric landslide analysis, 12 studies were selected for inclusion in the detailed synthesis presented in this paper.

Selection criteria for studies presented in Table 2. The 12 studies cited in this review and summarized in Table 2 were selected according to the following criteria:

- The study employs at least one AI or ML method applied to photogrammetric or remote sensing data for a landslide-related task;
- The study reports quantitative performance metrics (precision, recall, F1, IoU, RMSE, or equivalents);
- The study was published in a Web of Science or Scopus-indexed journal;
- The study contributes a methodologically distinct approach or application context not covered by other selected papers. Studies were chosen to provide a representative cross-section of architectural approaches (encoder–decoder segmentation, instance segmentation, lightweight CNNs, and physics-informed learning), training strategies (supervised, semi-supervised, transfer learning, and self-supervised), and performance benchmarks across diverse operational contexts.

This selection strategy prioritizes methodological diversity and geographic representativeness over exhaustive enumeration.

Topics covered. The review encompasses six primary application tasks: landslide detection and inventory mapping, landslide susceptibility mapping, semantic segmentation of landslide features, displacement monitoring and 3D modeling, DEM differencing and volumetric change analysis, and support for risk assessment and early warning. These tasks are explicitly delimited in Table 1, given that they differ substantially in their input data requirements, validation approaches, and appropriate performance indicators.

Table 1. Delimitation of primary application tasks in AI-driven photogrammetric landslide science

Task	Objective	Primary Input Data	Key Performance Indicators	Representative Studies
1. Landslide Detection & Inventory Mapping	Binary/multi-class landslide delineation	UAV/satellite orthomosaic, DSM	Precision, Recall, F1, mIoU	Ghorbanzadeh et al. (2019); Su et al. (2021); Kariminejad et al. (2024)
2. Susceptibility Mapping	Spatial probability of future occurrence	Terrain attributes, inventory polygons	ROC-AUC, Accuracy	Sevgen et al. (2019); Chen et al. (2023)
3. Semantic Segmentation	Fine-grained morphological feature delineation	High-res UAV imagery (≤5 cm GSD)	Boundary F1, Hausdorff distance, IoU	Șandric et al. (2024); Zhang et al. (2023)
4. Displacement Monitoring	Surface displacement quantification	Multi-epoch DSMs, point clouds	RMSE, MAE, displacement vector accuracy	Li et al. (2024); Lelli et al. (2025); Senogles et al. (2022)
5. Volumetric Change Analysis	Erosion/deposition volume computation	Repeat UAV surveys, co-registered DEMs	Volume error, co-registration RMSE	Cheng et al. (2021); Cardenal et al. (2019)
6. Risk Assessment & Early Warning	Quantitative risk estimation, trigger thresholds	Multi-source fusion (optical, radar, GNSS)	Warning lead time, false alarm rate	Zhu et al. (2025); He et al. (2022)

Source: compiled by the authors from cited studies

Delimitation of Application Tasks. AI-driven photogrammetric landslide science encompasses multiple related but methodologically distinct application tasks, each requiring different input data, validation approaches, and performance indicators. Merging these tasks can obscure important differences in data requirements, model architectures, and operational constraints. This subsection explicitly delineates six primary application domains.

Task 1 – Landslide Detection and Inventory Mapping. This task involves the binary or multi-class classification of image pixels or objects as landslide versus non-landslide, producing spatial inventories of landslide bodies. Input data typically include UAV or satellite orthomosaics and DSMs. Validation is performed against manually digitized reference polygons, and performance is reported using precision, recall, F1-score, and mIoU. Representative studies include Ghorbanzadeh et al. (2019), Su et al. (2021), and Kariminejad et al. (2024).

Task 2 – Landslide Susceptibility Mapping. This task produces continuous probability or categorical susceptibility maps indicating the spatial likelihood of future landslide occurrence based on conditioning factors (slope, lithology, land use, and rainfall). It does not require post-event imagery and is validated against existing inventories using statistical accuracy measures. Representative studies include Sevgen et al. (2019) and Chen et al. (2023).

Task 3 – Semantic Segmentation of Landslide Features. This task extends inventory mapping to the fine-grained delineation of sub-landslide morphological elements – scarps, cracks, depletion zones, and accumulation lobes—requiring higher spatial resolution and more detailed ground truth. Performance is evaluated using boundary-sensitive metrics (boundary F1, Hausdorff distance) in addition to pixel-level IoU. Representative studies include Șandric et al. (2024) and Zhang et al. (2023).

Task 4 – Displacement Monitoring and 3D Modeling. This task quantifies surface displacements and volumetric changes through multi-epoch DEM differencing (DoD), sub-pixel optical flow, or physics-informed learning. Input data are multi-temporal point clouds, DSMs, or orthomosaics. Validation uses GNSS benchmarks, total station measurements, or synthetic ground truth, and performance is reported using RMSE, mean absolute error (MAE), or displacement vector accuracy. Representative studies include Li et al. (2024), Lelli et al. (2025), and Senogles et al. (2022).

Task 5 – DEM Differencing and Volumetric Change Analysis. A subcategory of Task 4, this task focuses specifically on the computation of erosion and deposition volumes from repeat UAV surveys. It relies on accurate co-registration and uncertainty propagation rather than AI classification per se, though ML methods are increasingly used for outlier filtering and uncertainty estimation. Representative studies include Cheng et al. (2021) and Cardenal et al. (2019).

Task 6 – Risk Assessment and Early Warning Support. This task integrates outputs from Tasks 1–5 with hydrological, meteorological, and exposure data to produce quantitative risk estimates or trigger thresholds for early warning systems. AI contributes to the automation of feature extraction and the rapid updating of susceptibility and intensity maps following triggering events. Representative studies include Zhu et al. (2025) and He et al. (2022).

UAV Photogrammetry and Structure-from-Motion Workflows. UAV-based photogrammetric surveys have become the primary data acquisition modality for high-resolution landslide mapping and monitoring. The standard workflow follows a Structure-from-Motion / Multi-View Stereo (SfM-MVS) pipeline: overlapping nadir and oblique images are acquired at flight altitudes typically between 50 and 200 m above ground level, yielding ground sampling distances (GSDs) of 2–10 cm; SfM algorithms recover camera orientations and sparse point clouds from feature correspondences across image pairs; MVS densification produces dense point clouds with millions to billions of points per survey; and rasterization yields DSMs, DTMs, and orthomosaics that serve as inputs to AI-based analysis (Cheng et al., 2021; Cardenal et al., 2019). A typical UAV-SfM photogrammetric workflow for landslide mapping, showing image acquisition, dense point cloud generation, DSM/orthomosaic production, and AI-based classification is shown in Fig. 1.

The seven-phase AI-photogrammetry integration workflow can be described as follows:

Phase 1: Mission Planning
└─ Flight parameters (altitude, overlap, GSD target)
└─ GCP distribution and RTK-GNSS survey

Phase 2: UAV Image Acquisition
└─ Nadir + oblique imagery (RGB, multispectral, thermal)
└─ Simultaneous LiDAR scanning (optional)

Phase 3: SfM-MVS Processing
└─ Feature detection and matching (SIFT/ORB)
└─ Bundle adjustment → sparse point cloud
└─ MVS densification → dense point cloud

Phase 4: Product Generation
└─ DSM / DTM rasterization
└─ Orthomosaic generation
└─ Uncertainty / error map computation

Phase 5: AI-Based Analysis
└─ Input preparation (tiling, normalization, augmentation)
└─ Model inference (CNN / Transformer / Mask R-CNN)
└─ Post-processing (CRF, morphological filtering)

Phase 6: Validation and Accuracy Assessment
└─ Comparison with reference inventory / GNSS benchmarks
└─ Metric computation (F1, IoU, RMSE)

Phase 7: Operational Output
└─ Landslide inventory / susceptibility map
└─ Displacement map / volumetric change report
└─ Early warning integration

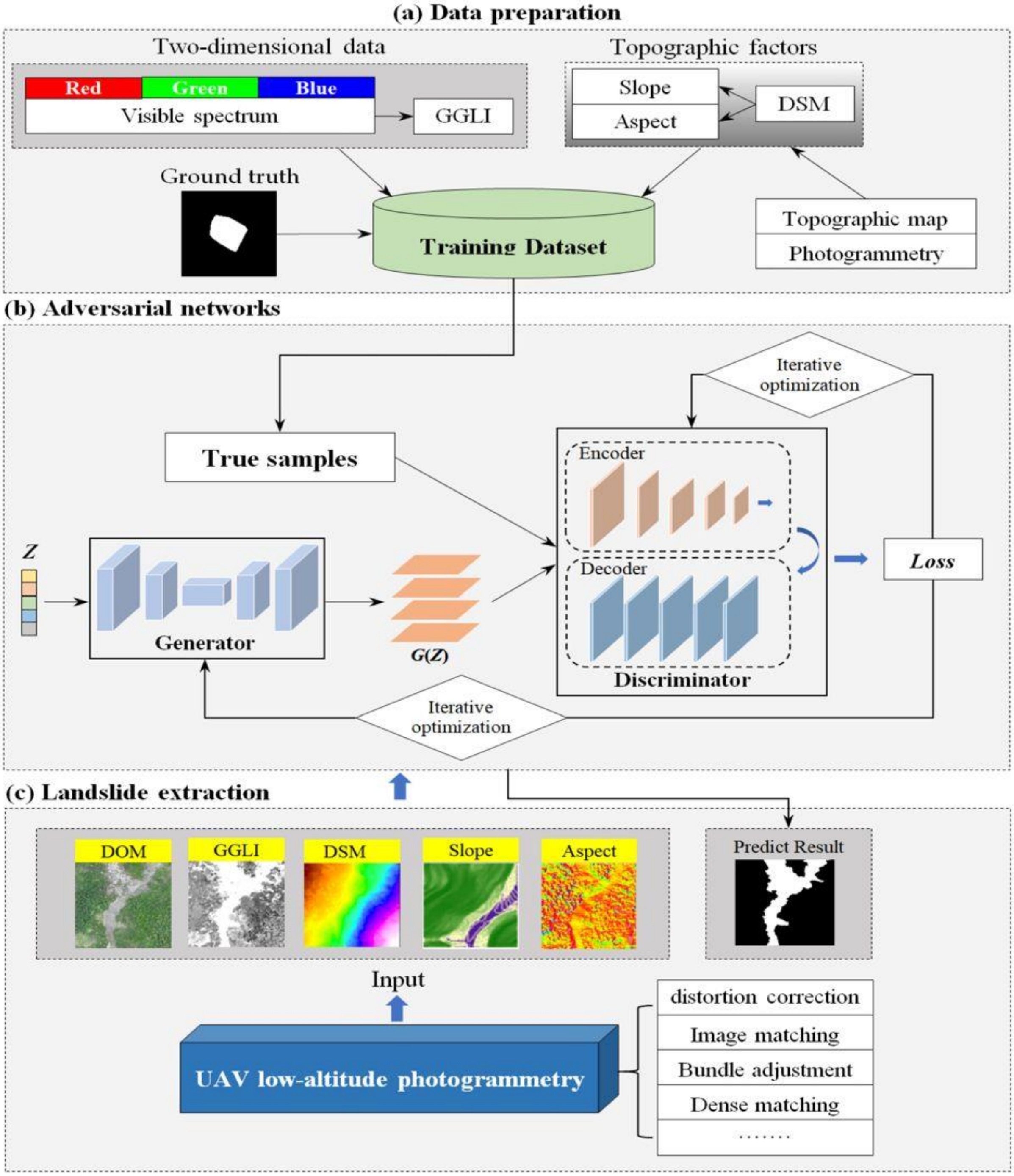

Fig. 1. Typical UAV-SfM photogrammetric workflow for landslide mapping
Source: He et al., 2022

Georeferencing accuracy is critical for change detection and displacement monitoring applications. According to Cardenal et al. (2019), planar accuracies of approximately ±0.02 m and vertical accuracies of ±0.04 m are achievable for UAV photogrammetric DEMs of road deformation sites with adequate Ground Control Point (GCP) distribution and RTK-GNSS support. Cheng et al. (2021) employed a similar workflow to characterize the kinematics of a landslide in Guizhou, China, using multi-epoch DSMs to quantify volumetric changes and identify reactivation zones.

The combination of UAV photogrammetry with LiDAR scanning further enhances monitoring capability. Lelli et al. (2025) deployed high-frequency UAV–LiDAR surveys at the Baldiola earthflow in the Northern Apennines, Italy, demonstrating that repeat point cloud differencing at weekly to monthly intervals could resolve displacement patterns and seasonal reactivation cycles at decimetric resolution. Li et al. (2024) integrated UAV photogrammetry with sub-pixel offset tracking to monitor the Wulipo landslide at the Baihetan Reservoir, China, quantifying horizontal displacements and identifying the primary deformation mechanism through time-series analysis. These multi-sensor approaches improve robustness but also increase data processing complexity and cost, factors that must be carefully weighed against operational requirements.

Deep Learning Architectures for Landslide Detection.

Encoder–Decoder Segmentation Networks. The U-Net architecture, originally developed for biomedical image segmentation, has been widely adopted for landslide delineation due to its ability to combine high-level semantic features with low-level spatial detail through skip connections. Șandric et al. (2024) applied U-Net alongside DeepLab variants to UAV imagery for crack detection, demonstrating that larger tile sizes and masked training samples substantially improved boundary fidelity. He et al. (2022) extended DeepLabv3+ with a topographic CNN encoder branch and multilevel skip connections, enabling the simultaneous exploitation of spectral reflectance and elevation derivatives for boundary-preserving segmentation. Kariminejad et al. (2024) benchmarked ResU-Net, MA-Net, and attention-augmented U-Net variants, finding that residual connections and attention gates consistently improved recall and mIoU for small or indistinct landslide bodies in semi-arid terrain. Chen et al. (2023) proposed a susceptibility-guided detection framework using fully convolutional networks, leveraging prior susceptibility maps to focus model attention on high-probability zones and reduce false positives in complex urban-adjacent terrain on Lantau Island, Hong Kong. While this susceptibility-guided approach is methodologically innovative, it introduces a dependency on pre-existing susceptibility maps whose quality and currency can significantly affect detection results.

Instance Segmentation and Object Detection. For applications requiring the delineation of individual landslide bodies – particularly in densely affected areas or where instance-level inventory statistics are needed – Mask R-CNN and its variants have been widely applied. Liu et al. (2021) developed an improved Mask R-CNN with a ResNeXt backbone for automated landslide extraction in Jiuzhaigou County, Sichuan Province, China, reporting precision of 95.8%, recall of 93.1%, and overall accuracy of 94.7% (Table 1). Zhang et al. (2023) further enhanced Mask R-CNN with a Convolutional Block Attention Module (CBAM) and a Guided Anchoring Region Proposal Network (GA-RPN), achieving recall of 91.4% and accuracy of 92.6% on UAV imagery from Sanming City, China – improvements of approximately 10–13 percentage points over the baseline model (Table 1).

Lightweight and Multi-Scale Networks. Recognizing the computational demands of large-scale DL models, several studies have proposed lightweight architectures optimized for operational deployment. Lu et al. (2024) introduced MS2LandsNet, a multi-scale feature fusion CNN with multi-scale channel attention, designed for efficient landslide detection from medium-resolution remote sensing data. The results from the improved R_CNN model with the CBAM attention module, applied to UAV imagery, are shown in Fig. 2. The network achieved F1 of 85.90% and IoU of 75.28% while requiring substantially fewer parameters than transformer-based alternatives, making it suitable for near-real-time processing pipelines. However, the trade-off between model compactness and detection accuracy for small or morphologically complex landslide bodies remains an open research question that warrants further systematic evaluation.

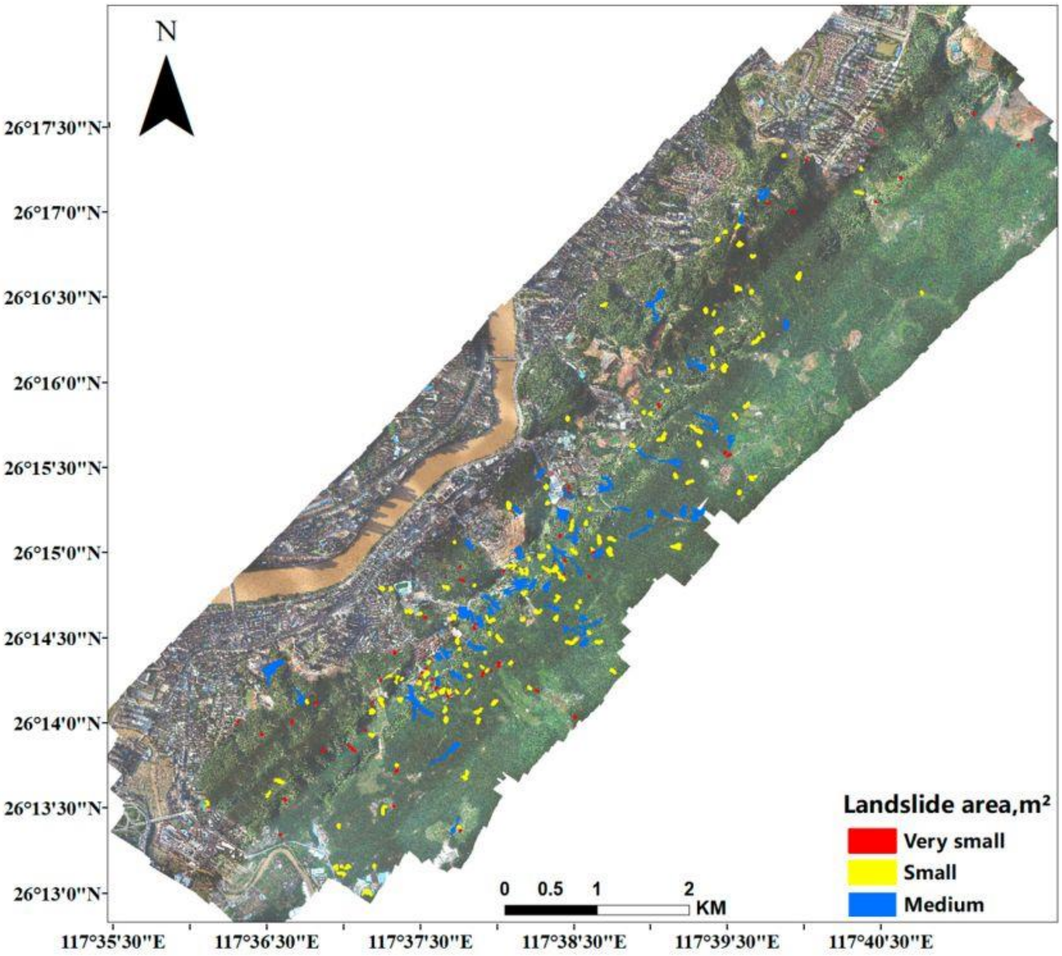

Fig. 2. Landslide detection results from the improved Mask R-CNN model with the CBAM attention module applied to UAV imagery in Sanming, China
Source: Zhang et al. ,2023

Training Strategies. Transfer learning mitigates the scarcity of labeled landslide samples by initializing model weights from networks pre-trained on large-scale image datasets (e.g., ImageNet) and fine-tuning on domain-specific UAV data. Yang et al. (2022) demonstrated that transfer learning substantially improved landslide recognition on UAV imagery from the Zhangmu Port region, Tibet, particularly when labeled samples were limited following the 2015 Nepal earthquake. Despite its effectiveness, transfer learning may introduce domain shift artifacts when the source and target domains differ substantially in spatial resolution, spectral characteristics, or terrain morphology – a limitation that requires careful validation.

Semi-supervised adversarial training further reduces labeled-data requirements by leveraging unlabeled multisource inputs. He et al. (2022) introduced a semi-supervised generative adversarial framework in which a pix2pix-style generator learned semantic features from unlabelled UAV photogrammetry products, while the discriminator (an enhanced DeepLabv3+) refined segmentation boundaries through adversarial feedback. This approach improved all performance metrics by 13–18 percentage points relative to supervised-only baselines, demonstrating the practical value of semi-supervised strategies in data-scarce scenarios.

Data augmentation strategies – including random cropping, flipping, rotation, color jitter, and large-tile mosaicking – are routinely applied to increase effective training set size and improve model robustness to viewpoint and illumination variation (Zhang et al., 2023; Zhu et al., 2025). While augmentation is a well-established best practice, its interaction with class imbalance and the representativeness of the augmented distribution relative to real-world variability deserves more systematic investigation in landslide applications.

Displacement Monitoring and 3D Modeling. Beyond inventory mapping, UAV photogrammetry supports quantitative displacement monitoring through DEM of Difference (DoD) analysis, sub-pixel optical flow, and physics-informed learning. Li et al. (2024) applied sub-pixel offset tracking to multi-epoch UAV orthomosaics of the Wulipo landslide, resolving horizontal displacement vectors with sub-decimetric precision and identifying the primary failure mechanism as translational sliding along a basal shear surface. Lelli et al. (2025) used high-frequency UAV–LiDAR surveys to track earthflow kinematics at the Baldiola landslide, demonstrating that seasonal velocity cycles could be resolved at weekly temporal sampling.

Senogles et al. (2022) proposed SlideSim, a self-supervised framework that synthesises physically plausible landslide displacement fields using a DEM-based simulation engine, then trains an optical-flow predictor on the synthetic data. Applied to the southern Oregon coast, USA, SlideSim achieved an endpoint RMSE of 0.026 m against dense ground truth—a result competitive with supervised approaches while requiring no manually labeled displacement data. This physics-based simulation approach represents a promising direction for reducing annotation burden in displacement monitoring, though its generalisability to diverse geomorphological settings and landslide types requires further evaluation.

Results and discussion

Table 2 summarizes reported performance metrics across representative studies reviewed in this paper. Important note: The diversity of study areas, sensor configurations, input bands, evaluation protocols, and ground truth quality precludes direct numeric comparisons between studies. Performance indicators are highly context-dependent, influenced by factors including landslide size and morphology, terrain complexity, vegetation cover, image resolution, class balance in training data, and validation methodology. Furthermore, the studies included in Table 2 therefore serves as a qualitative overview of representative studies and reported performance ranges, rather than as a quantitative benchmark for ranking methods. Readers are cautioned against interpreting numeric differences across studies as evidence of superior performance without considering the specific operational context, application task, and validation approach of each study.

Table 2. Comparative performance metrics of AI-based landslide detection and monitoring methods across selected studies

Study and Study Area	**Method**	**Key Performance Metrics**
Ghorbanzadeh et al. (2019), Northern Himalayas, India	CNN semantic segmentation with slope input	Precision ≈90%, F-score 85%, mIoU 74%
Şandric et al. (2024), Multiple sites (crack detection)	U-Net and DeepLab; masked 512px tiles	F1 >0.93 (masked 512px) vs. ~0.79 (non-masked 64px)
He et al. (2022), Meilong gully, China	Semi-supervised adversarial nets + DeepLabv3+ dual-encoder	Precision/Recall/F1/mIoU improved ~13–18% vs. baseline DeepLabv3+
Karantanellis et al. (2021), Greece, Romania, Turkey	OBIA + DSM + Random Forest	Best F1 = 0.85 (with DSM + RF)
Kariminejad et al. (2024), Golestan Province, Iran	ResU-Net, Attention U-Net, MA-Net	Best landslide F1 = 0.95; ResU-Net Precision 0.97, Recall 0.92
Zhu et al. (2025), Wanli District, Nanchang, China	U-Net-based automated system	mIoU 90.7%, Pixel Accuracy 92.3%
Li et al. (2024), Baihetan Reservoir, China	DeepLab4LS (dual-encoder)	mIoU 76.0% (5.5 pp improvement over DeepLabv3+)
Zhang et al. (2023), Sanming, China	Improved Mask R-CNN with CBAM + GA-RPN	Recall 91.4%, Accuracy 92.6% (~10–13% improvement vs. baseline)
Liu et al. (2021), Jiuzhaigou County, Sichuan, China	Improved Mask R-CNN with ResNeXt-101	Precision 95.8%, Recall 93.1%, OA 94.7%
Su et al. (2021), Lantau Island, Hong Kong	LanDCNN segmentation	Highest F1 among cases; ~3 min for 25 km^2 at 0.5 m resolution
Lu et al. (2024), Multi-dataset benchmark	MS2LandsNet lightweight CNN	F1 85.90%, IoU 75.28% with minimal parameters
Senogles et al. (2022), Southern Oregon Coast, USA	SlideSim self-supervised DEM flow predictor	Endpoint RMSE = 0.026 m vs. dense ground truth

Source: compiled by the authors from cited studies

Advantages of AI-photogrammetry integration lead to the following:

- Higher delineation accuracy and throughput. Deep learning segmentation models consistently outperform OBIA and classical ML baselines in boundary fidelity and processing speed, enabling the rapid production of landslide inventories over large areas (Su et al., 2021; Ghorbanzadeh et al., 2019). The combination of spectral and topographic inputs further boosts performance by providing complementary discriminative information (He et al., 2022; Kariminejad et al., 2024).
- Label efficiency through transfer and semi-supervised learning. Transfer learning and adversarial semi-supervised frameworks substantially reduce the labeled data required for effective training, making AI-based mapping feasible in data-scarce post-disaster scenarios (Yang et al., 2022; He et al., 2022).
- Quantitative displacement monitoring. UAV photogrammetry combined with sub-pixel tracking and physics-informed learning enables the quantification of surface displacements with sub-decimetric precision, supporting the characterization of landslide kinematics and failure mechanisms (Li et al., 2024; Senogles et al., 2022; Lelli et al., 2025).
- Scalable, near-real-time pipelines. Lightweight architectures and tiling strategies enable processing throughputs compatible with emergency response timelines, with some systems targeting sub-minute per-km^2 inference rates (Lu et al., 2024; Zhu et al., 2025).
- Multi-source data fusion. The integration of UAV photogrammetry with LiDAR, GNSS, and multispectral sensors provides complementary geometric and spectral information, improving detection robustness across diverse terrain and vegetation conditions (Lelli et al., 2025; Li et al., 2024).

Besides significant advantages of AI-photogrammetry integration, there are still many **limitations and challenges:**

- Data scarcity and class imbalance. High-quality, spatially diverse, and temporally dense labeled datasets remain scarce. Most published studies are based on single sites or limited geographic regions, constraining the generalisability of trained models to new landscapes (Karantanellis et al., 2021; Kariminejad et al., 2024).
- Overfitting and poor transferability. Models trained on limited or geographically homogeneous datasets tend to overfit to local spectral and morphological signatures, performing poorly when applied to new study areas without retraining or domain adaptation (Su et al., 2021; Yang et al., 2022).
- Computational demands. Large-scale transformer architectures and multi-source fusion pipelines impose substantial computational requirements that may limit deployment in resource-constrained field settings, motivating the development of lightweight alternatives (Lu et al., 2024).
- Interpretability and explainability. The black-box nature of deep neural networks limits understanding of failure modes and reduces practitioner trust in automated outputs, particularly in high-stakes emergency response contexts (Chen et al., 2023).
- Preprocessing sensitivity. Model performance is sensitive to DEM resolution, tile size, input band configuration, and georeferencing accuracy, making it difficult to establish

universal best-practice pipelines applicable across sensors and study areas (Șandric et al., 2024; Zhang et al., 2023).

- Confusion with spectrally similar classes. Roads, bare agricultural fields, and river deposits can exhibit spectral and morphological characteristics similar to landslide scars, leading to false positives that require post-classification filtering (He et al., 2022; Zhang et al., 2023).
- Task-specific evaluation challenges. As highlighted in Table 2, different application tasks require fundamentally different evaluation frameworks. The absence of standardized, publicly available benchmark datasets for each task makes cross-study comparison difficult and may lead to overly optimistic performance claims when models are evaluated on in-distribution test sets (Karantanellis et al., 2021; Lu et al., 2024).

Conclusions

The integration of artificial intelligence with UAV and satellite photogrammetry has fundamentally transformed the science and practice of landslide detection, mapping, and monitoring. Deep learning architectures – particularly encoder–decoder segmentation networks, instance segmentation frameworks, and lightweight multi-scale CNNs – now achieve accuracy levels and processing speeds that were unattainable with manual or classical ML methods, enabling the production of detailed landslide inventories at spatial and temporal scales relevant to disaster risk reduction and land management (Ghorbanzadeh et al., 2019; Su et al., 2021; He et al., 2022).

At the same time, the field faces persistent challenges in data availability, model generalization, computational efficiency, and interpretability that must be addressed before AI-photogrammetric systems can be fully operationalized for real-time hazard monitoring and early warning.

The following research directions are identified as priorities for the coming decade:

1. **Explainable AI (XAI) and physics-aware models.** Integrating process-based understanding of slope mechanics with learned representations will improve model interpretability, support practitioner trust, and enable more physically consistent extrapolation to unobserved conditions (Chen et al., 2023).
2. **Multi-sensor fusion and standardized benchmarks.** Expanding and interlinking high-resolution, multi-sensor benchmark datasets – combining UAV optical imagery, LiDAR point clouds, GNSS displacement records, and SAR coherence products – will enable more robust cross-site generalization and facilitate rigorous comparative evaluation of competing architectures (He et al., 2022; Lelli et al., 2025).
3. **Real-time and cloud-scalable pipelines.** Lightweight models, streaming tiling strategies, and cloud-based inference platforms will enable near-real-time post-event mapping and early warning integration, directly supporting emergency response operations (Lu et al., 2024; Zhu et al., 2025).
4. **Self-supervised and physics-informed learning.** Broadening simulation-based approaches such as SlideSim (Senogles et al., 2022) to diverse geomorphological

settings will reduce dependence on manually labeled displacement data while maintaining physical plausibility.

5. **Operational validation and cost engineering.** Systematic field validation campaigns and runtime benchmarking studies are needed to quantify the accuracy–cost trade-offs of different architectures and inform the selection of deployment-ready solutions for national and regional hazard monitoring agencies (Lu et al., 2024; Sevgen et al., 2019).

In summary, AI-driven photogrammetric landslide science is advancing rapidly toward operational maturity. Sustained investment in data infrastructure, model explainability, and multi-sensor integration will be essential to realize the full potential of these technologies for global disaster risk reduction.

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Declaration of Competing Interests

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Data Availability

Publicly accessible data, including research papers with their DOIs listed in the references, support this study's findings.

Use of generative AI and AI-assisted technologies

Generative AI tools assisted in language refinement during the preparation of this manuscript. The authors reviewed and approved all final content.

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